Deep Learning-based Damage Mapping with InSAR Coherence Time Series

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Second AI and Data Science Workshop for Earth and Space Sciences — February 9–11, 2021

Feedback form: https://bit.ly/2OkRT41

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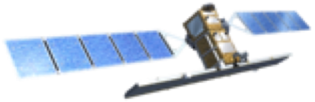
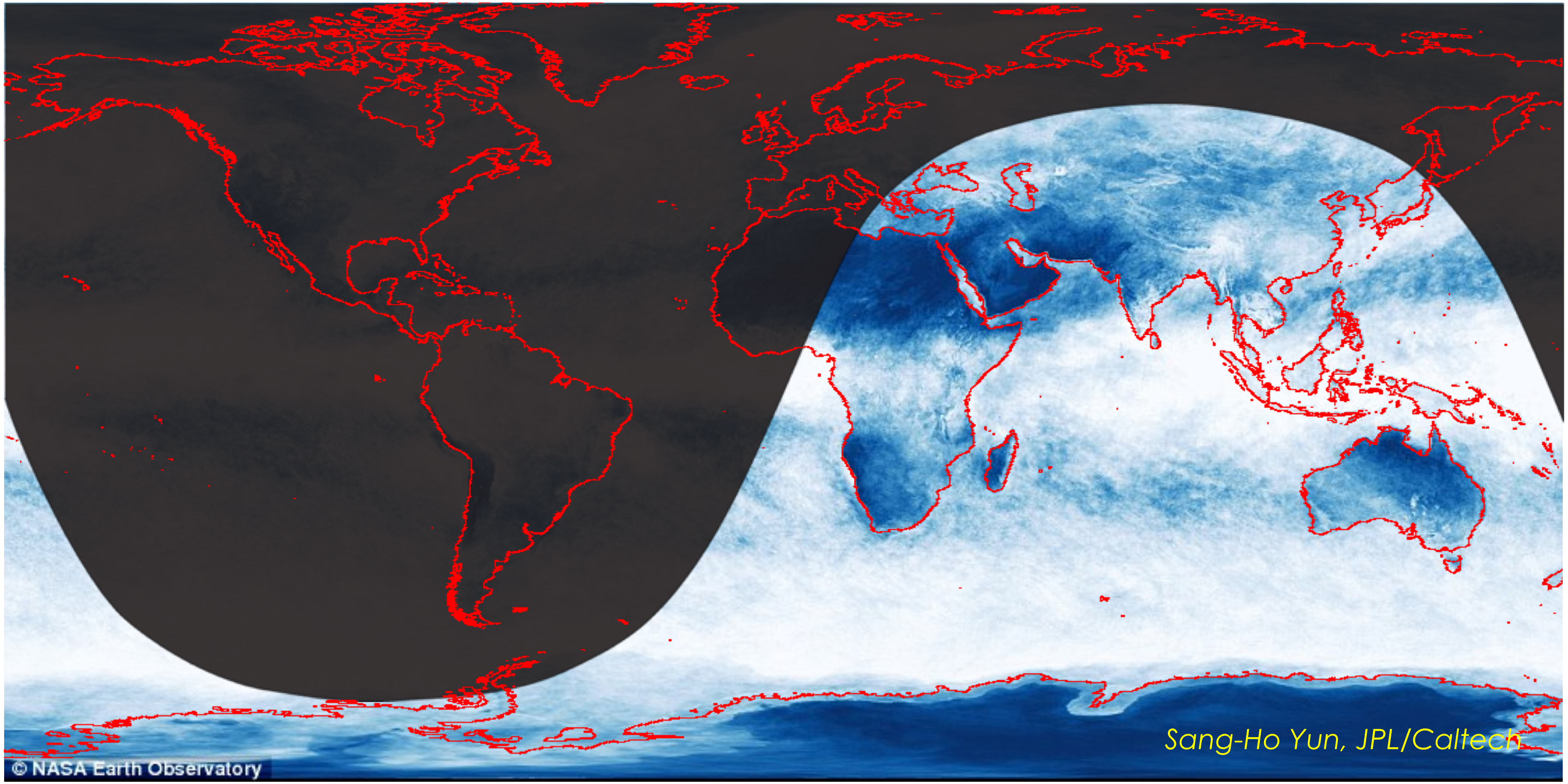
Stephenson *et al.*, IEEE Transactions on Geoscience and Remote Sensing (in revision)

Satellite radar data has key advantages





A ‘Golden Age’ of Satellite Radar

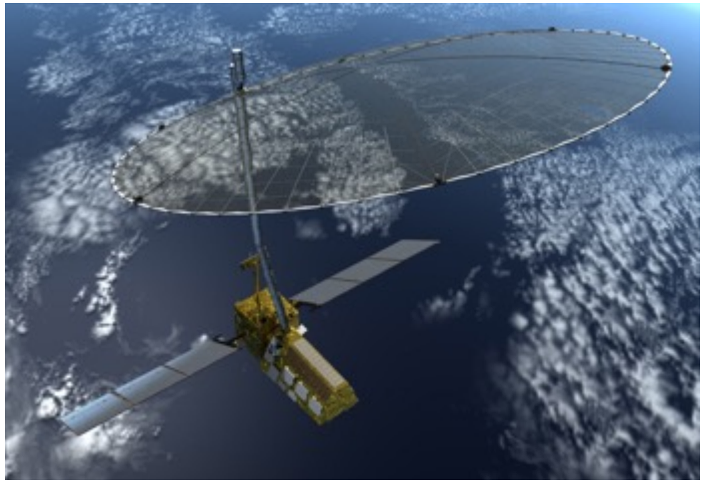
“A paradigm shift is…taking place in spaceborne SAR systems” — Alberto Moreira (2014), German Aerospace Center

Currently acquiring data:

Launching in the next few years:

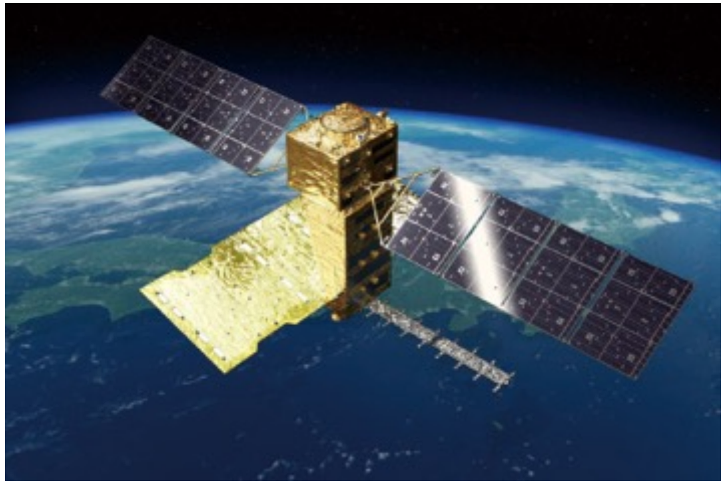
Sentinel 1-A/B

Image: ESA



NISAR

Image: NASA

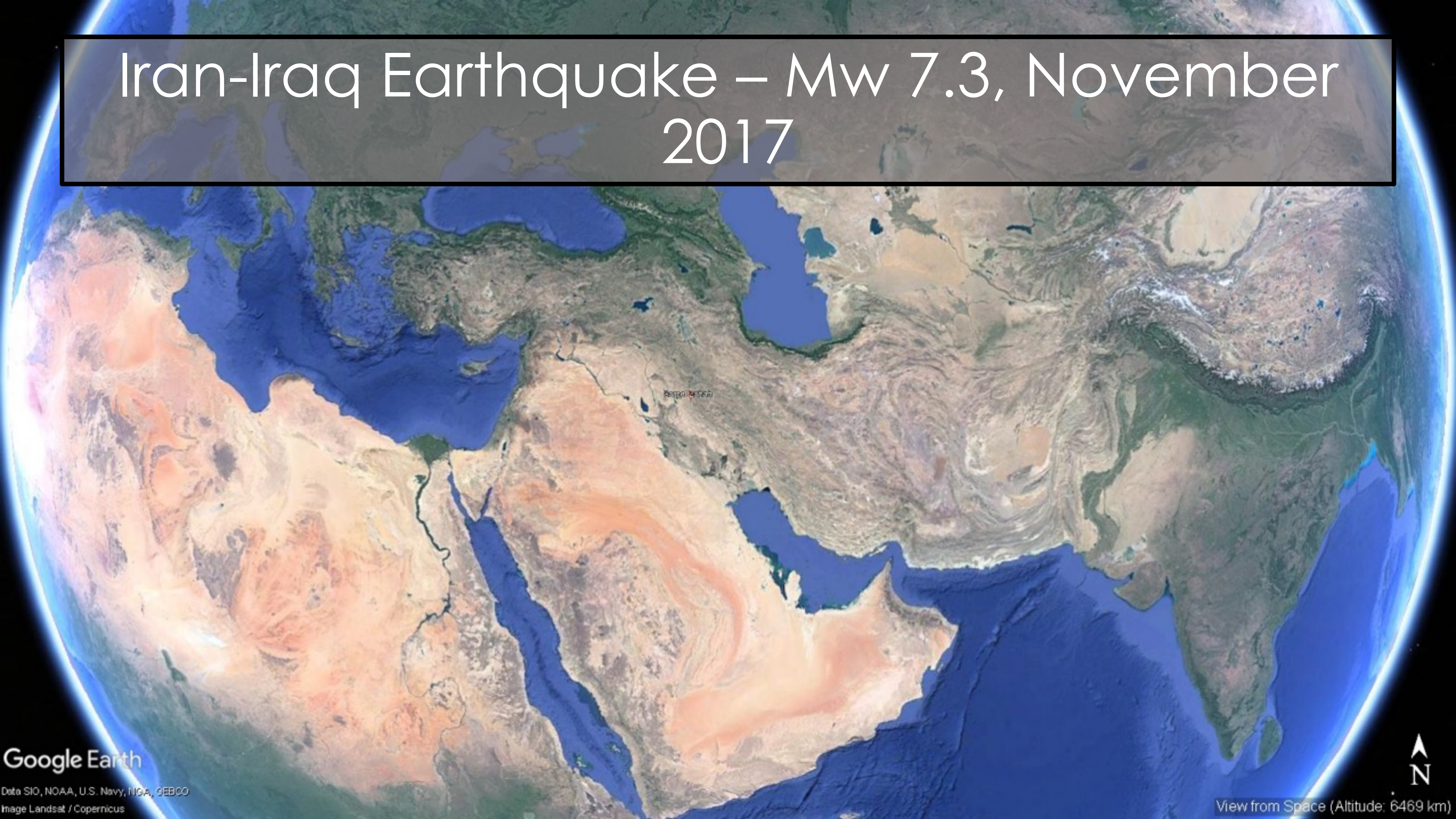


ALOS-4

Image: JAXA

How can we apply machine learning to large quantities of satellite based radar data to rapidly and reliably map damage in the event of major disasters?

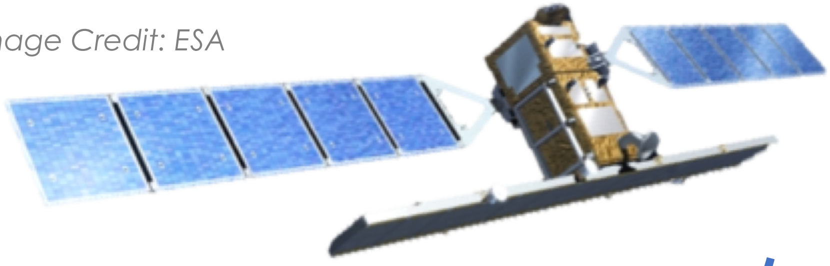
Iran-Iraq Earthquake – Mw 7.3, November 2017

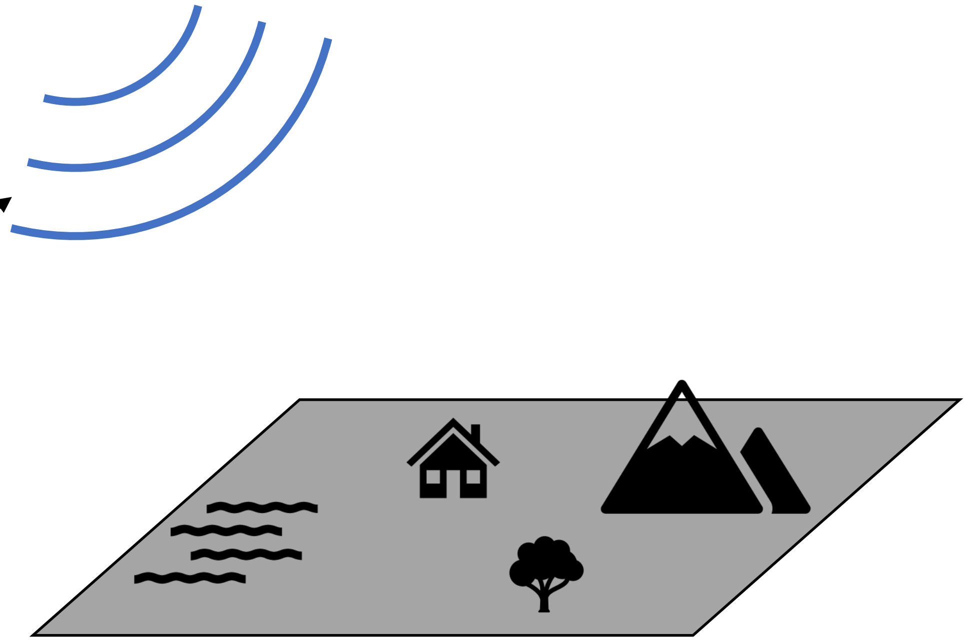


Iran-Iraq Earthquake – Mw 7.3, November 2017

Synthetic Aperture Radar (SAR)

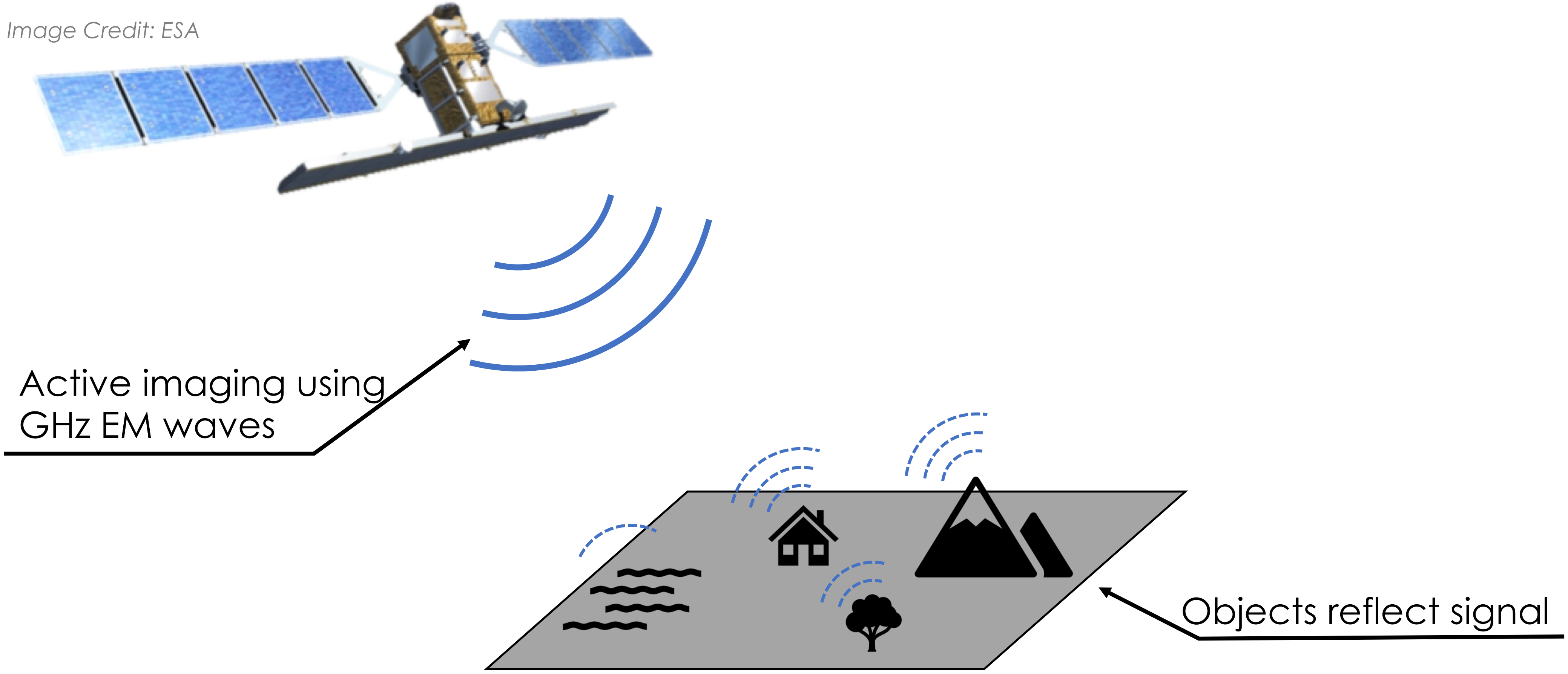
Image Credit: ESA





Active imaging using
GHz EM waves

Synthetic Aperture Radar (SAR)



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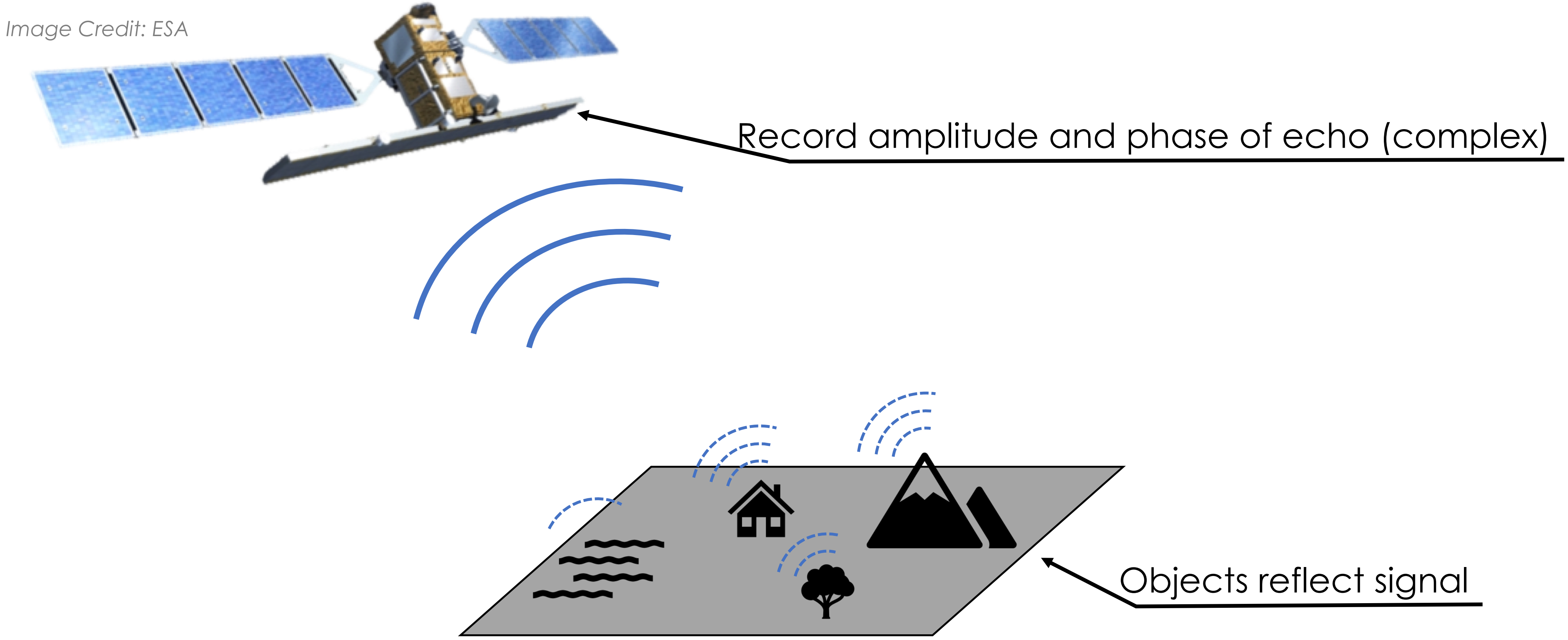

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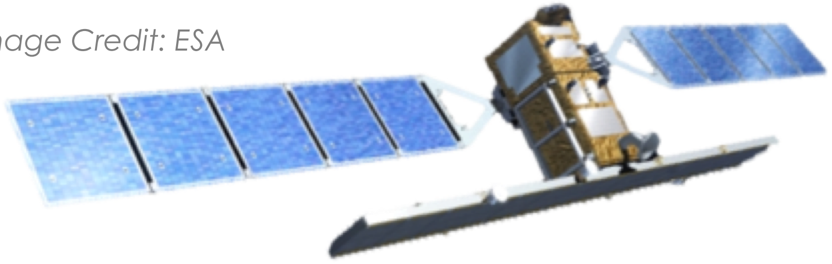
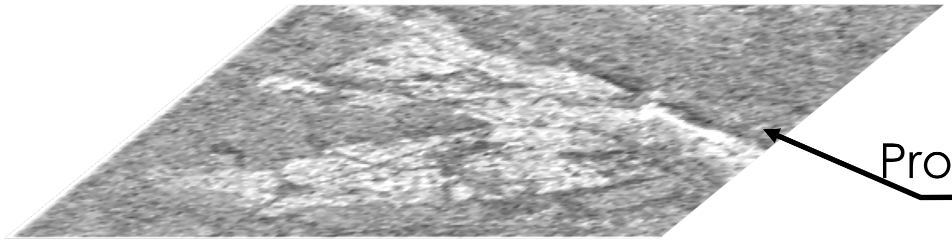
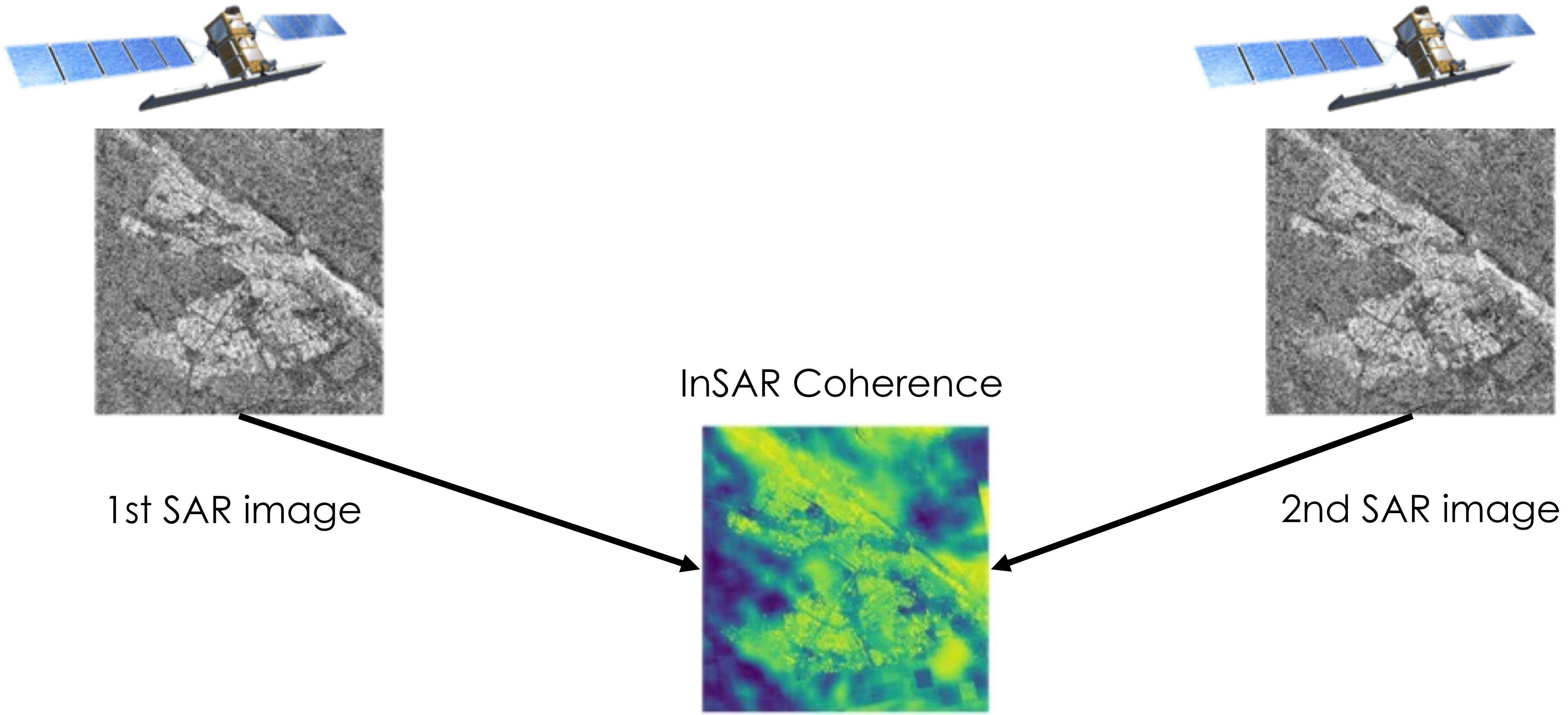




Process to get SAR Image

Look at changes between two SAR images: Interferometric Synthetic Aperture Radar (InSAR)

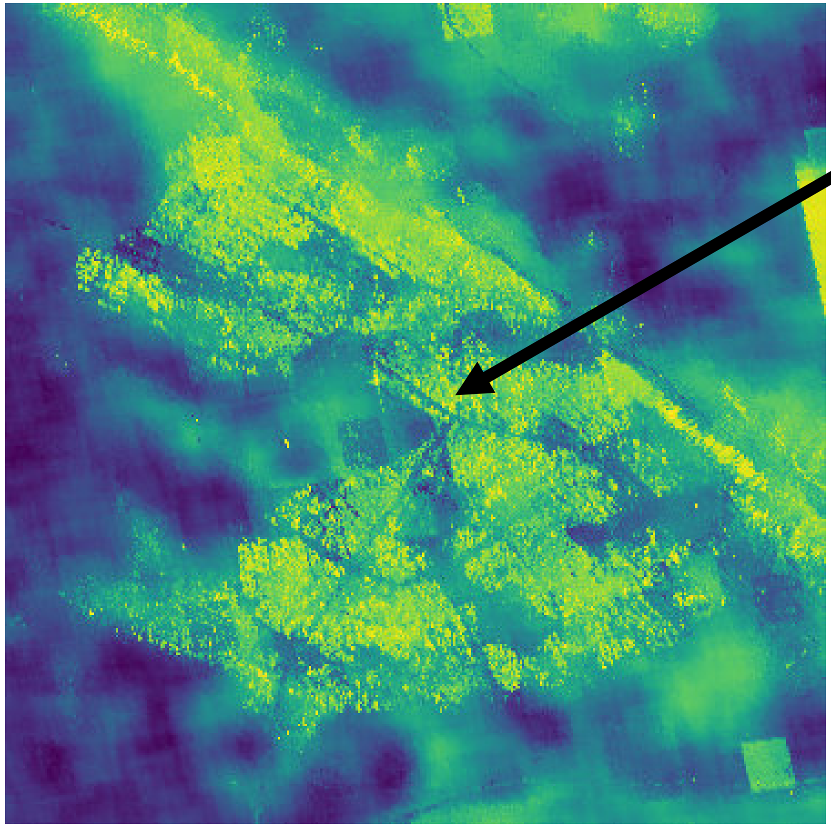


Small changes in the reflected radar waves means **high coherence**

Large changes in the reflected radar waves means **low coherence**

InSAR coherence is a measure of surface change

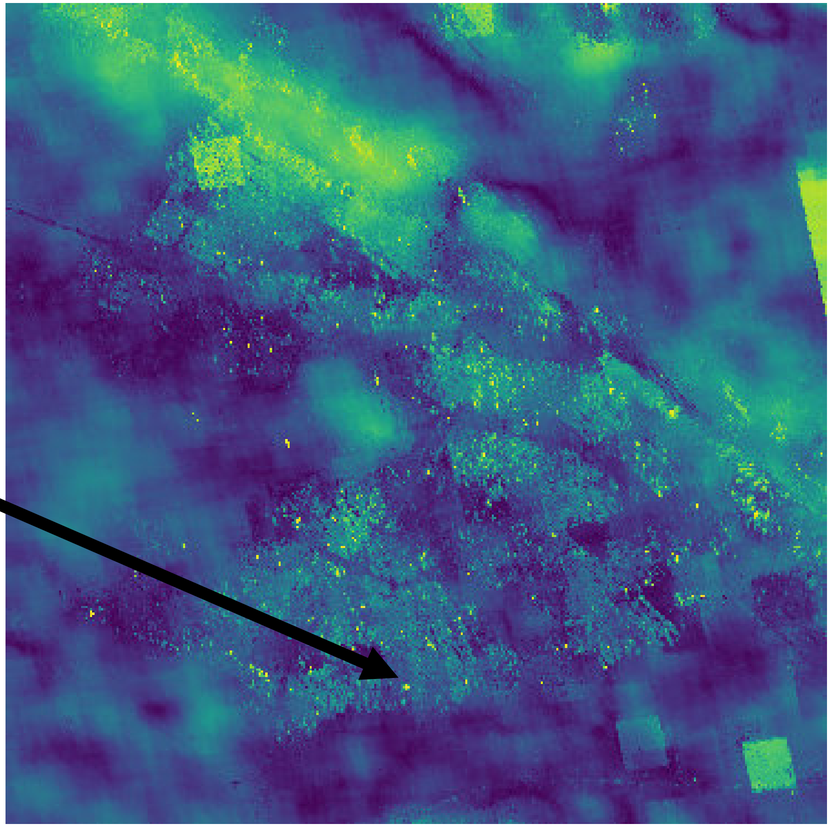
Pre-earthquake



Buildings are stable and reflect radar waves in the same way each time: **high coherence**

If the buildings collapse however, the radar reflection changes: **low coherence**

Spanning earthquake



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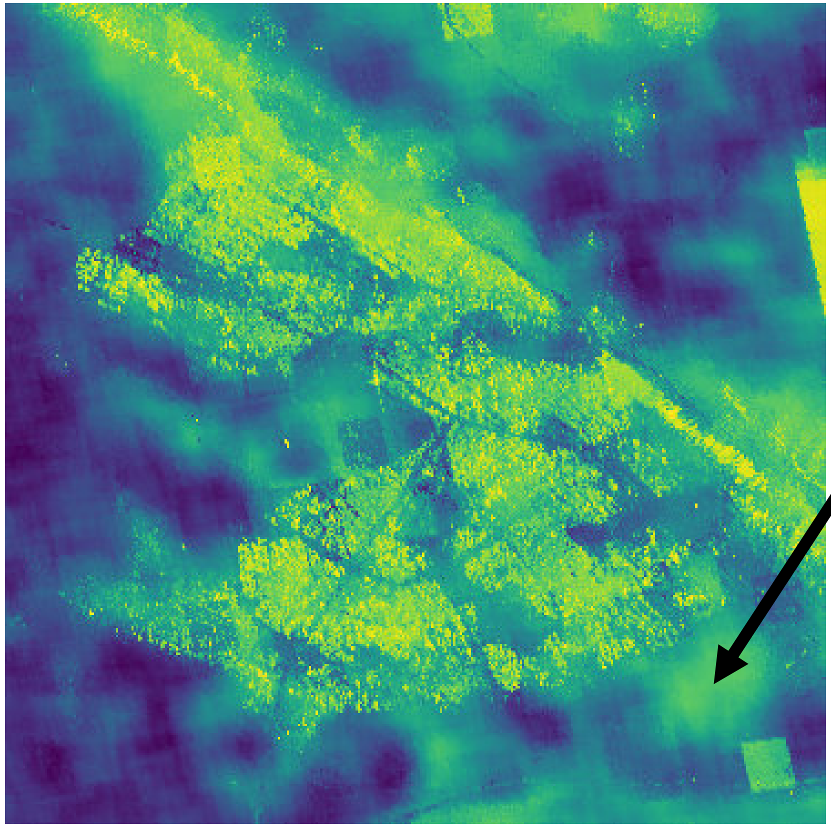
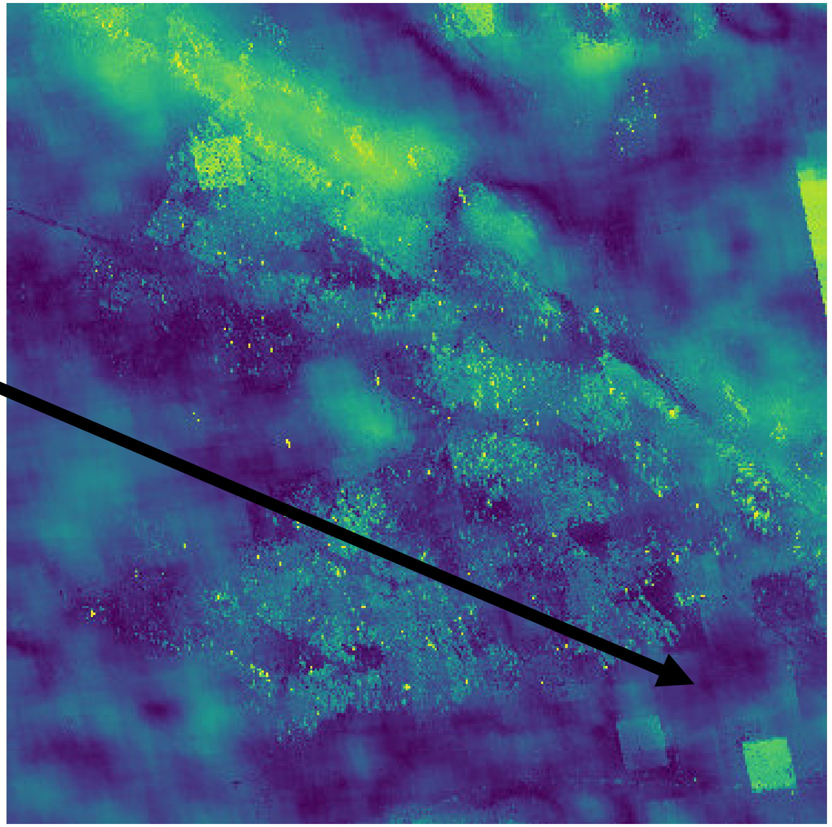


Spanning earthquake

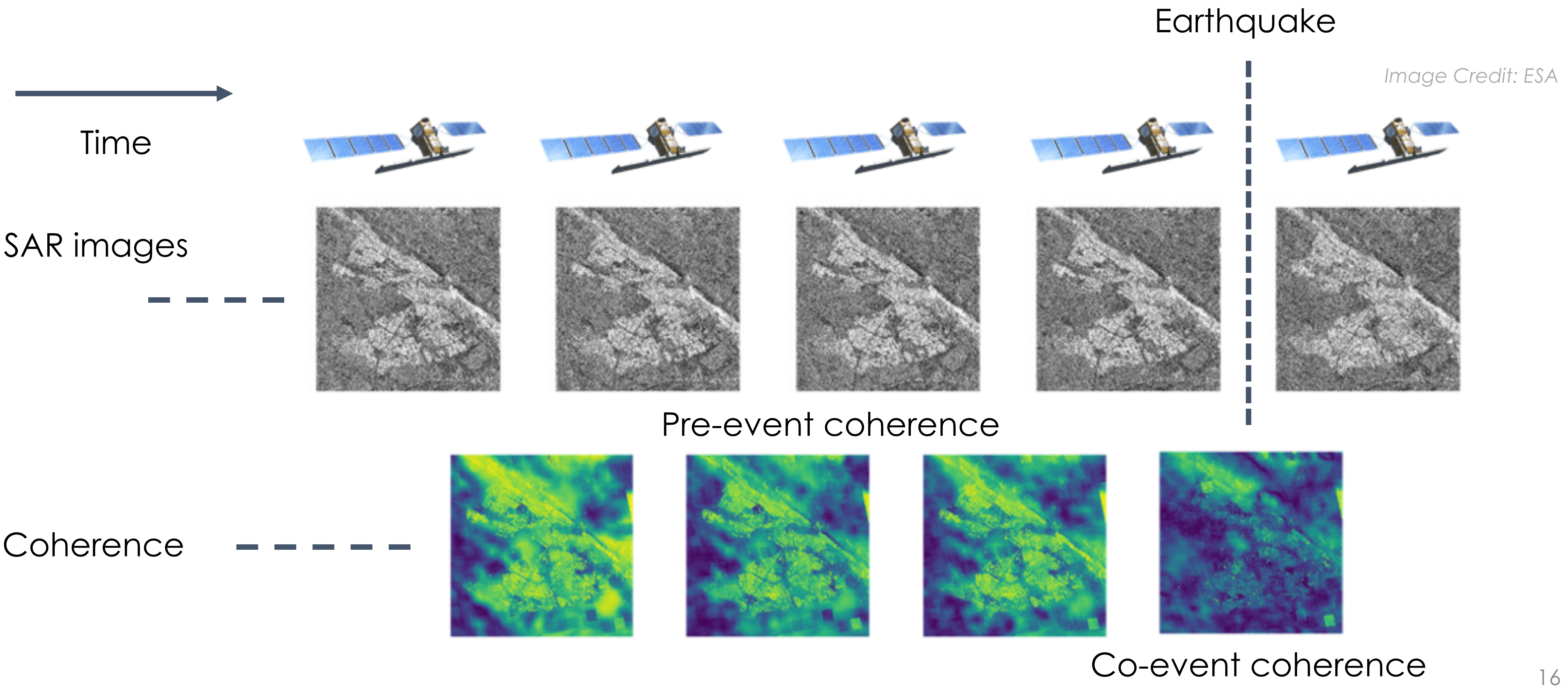


Some areas have very variable coherence

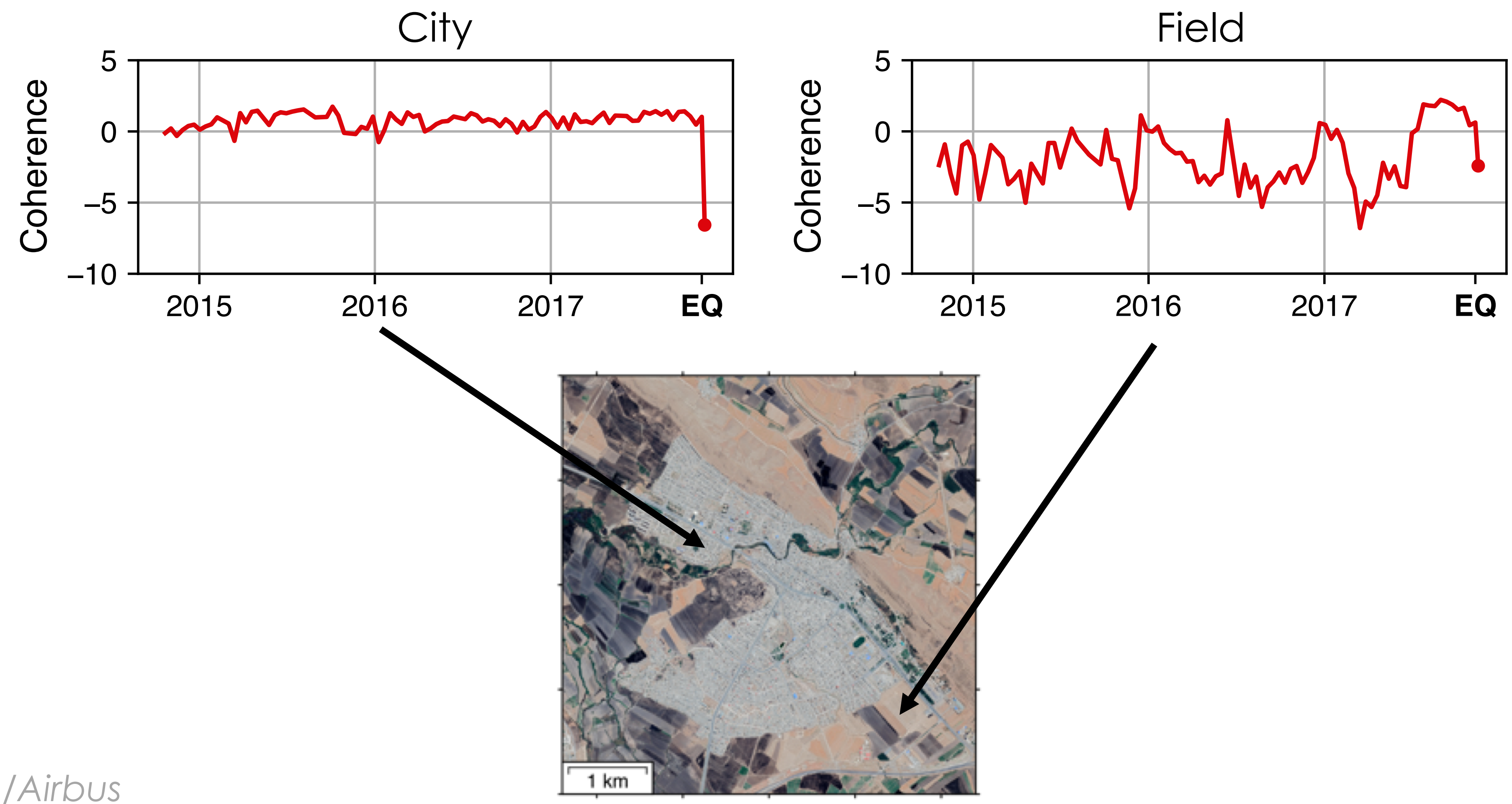
Low High

Coherence

We can get more information from sequential coherence

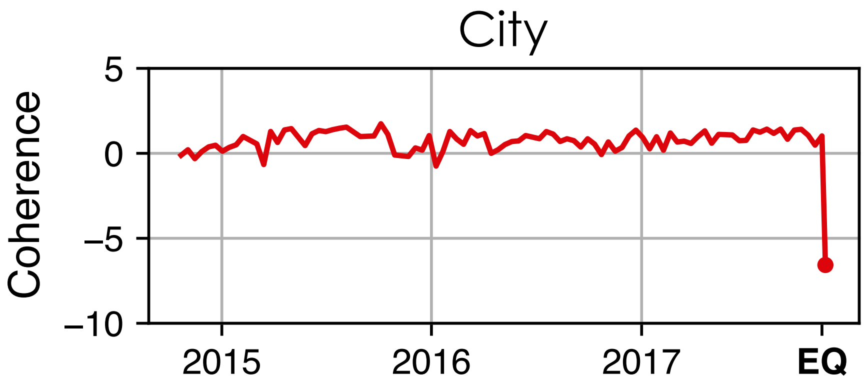


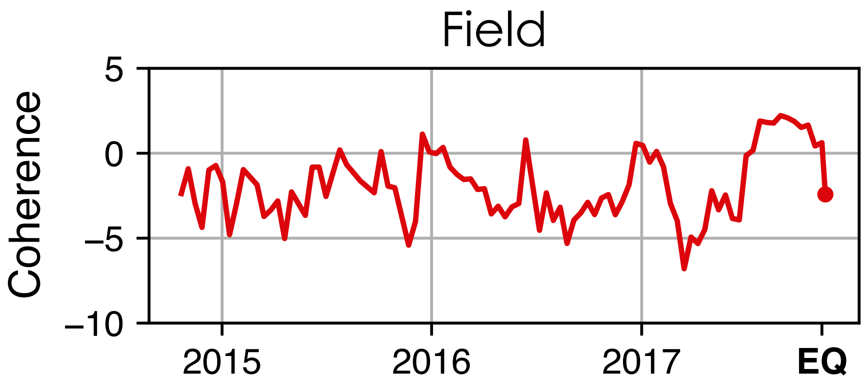
Each pixel has a coherence time series



Optical data: Google/CNES/Airbus

How can we reliably detect anomalies in coherence time series?





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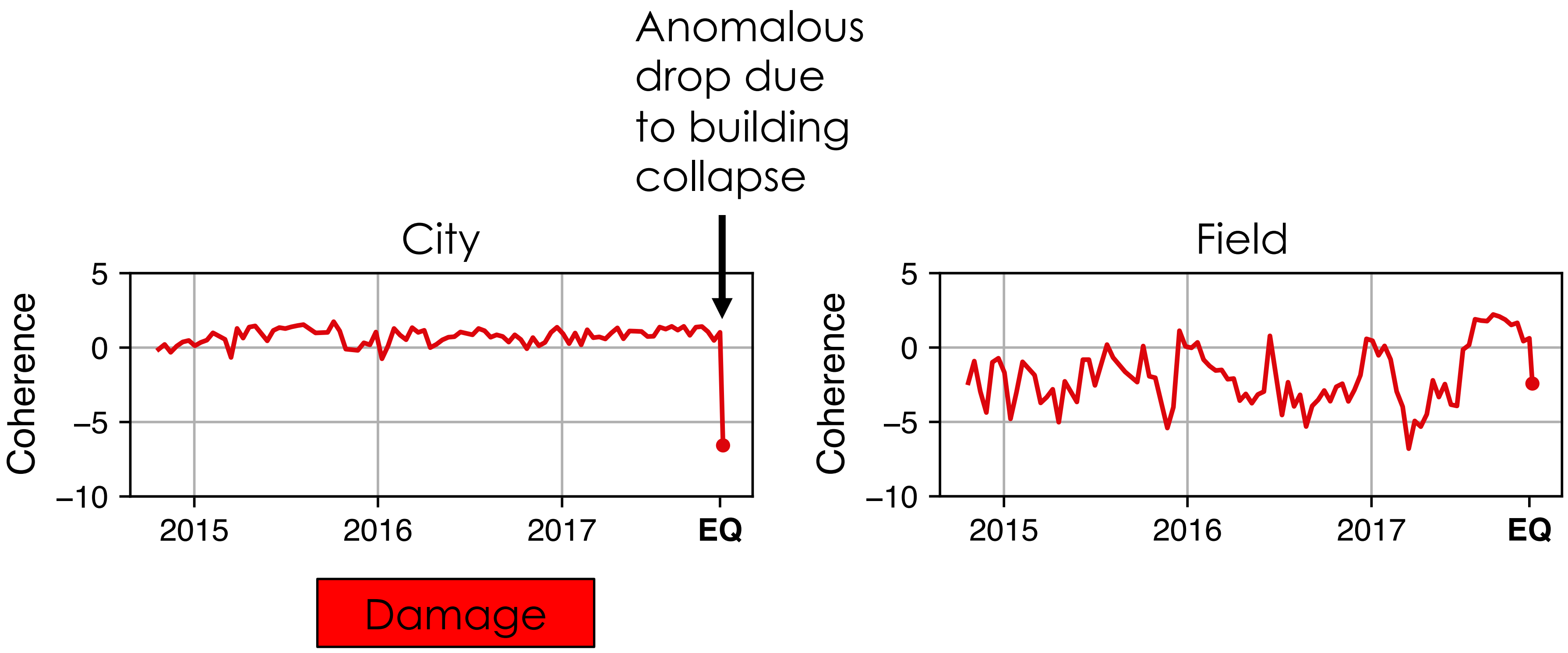

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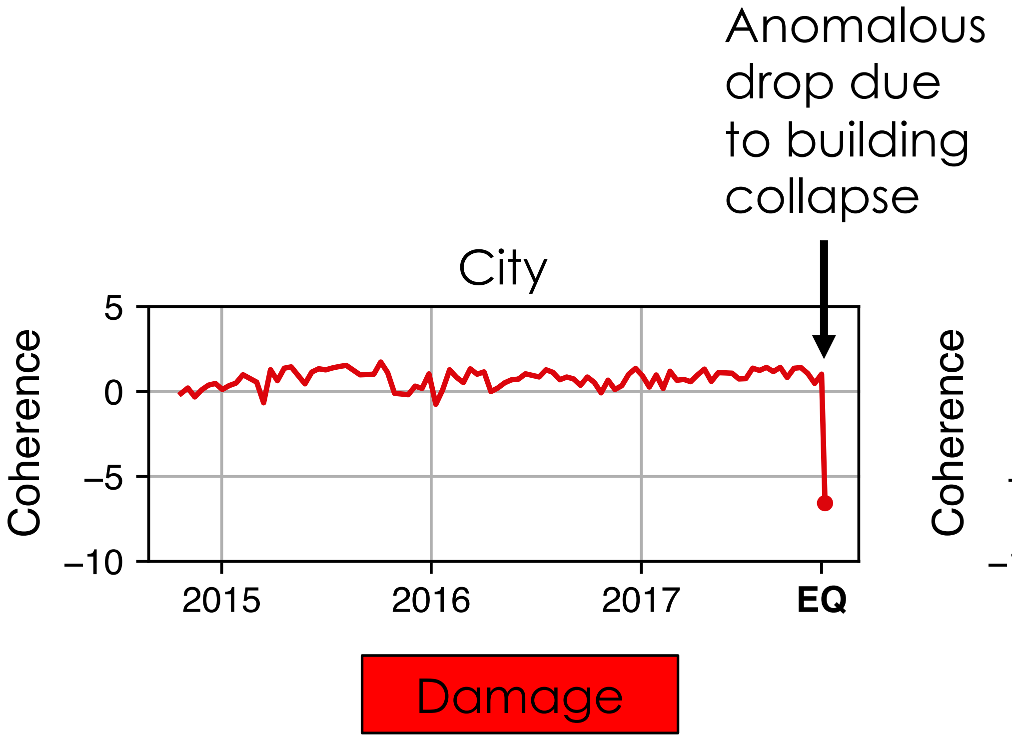
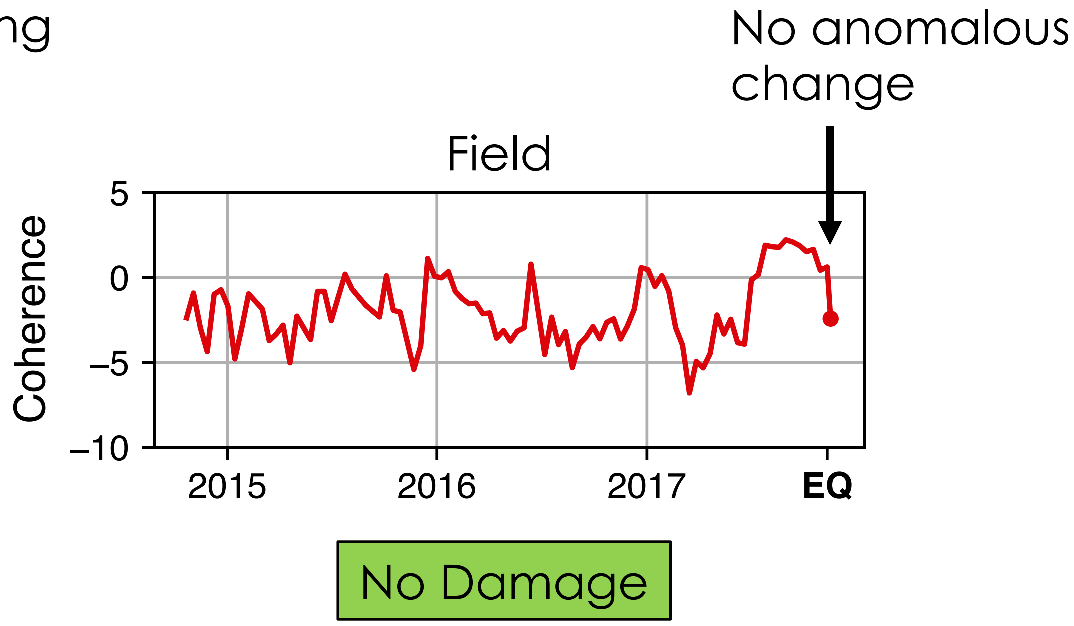
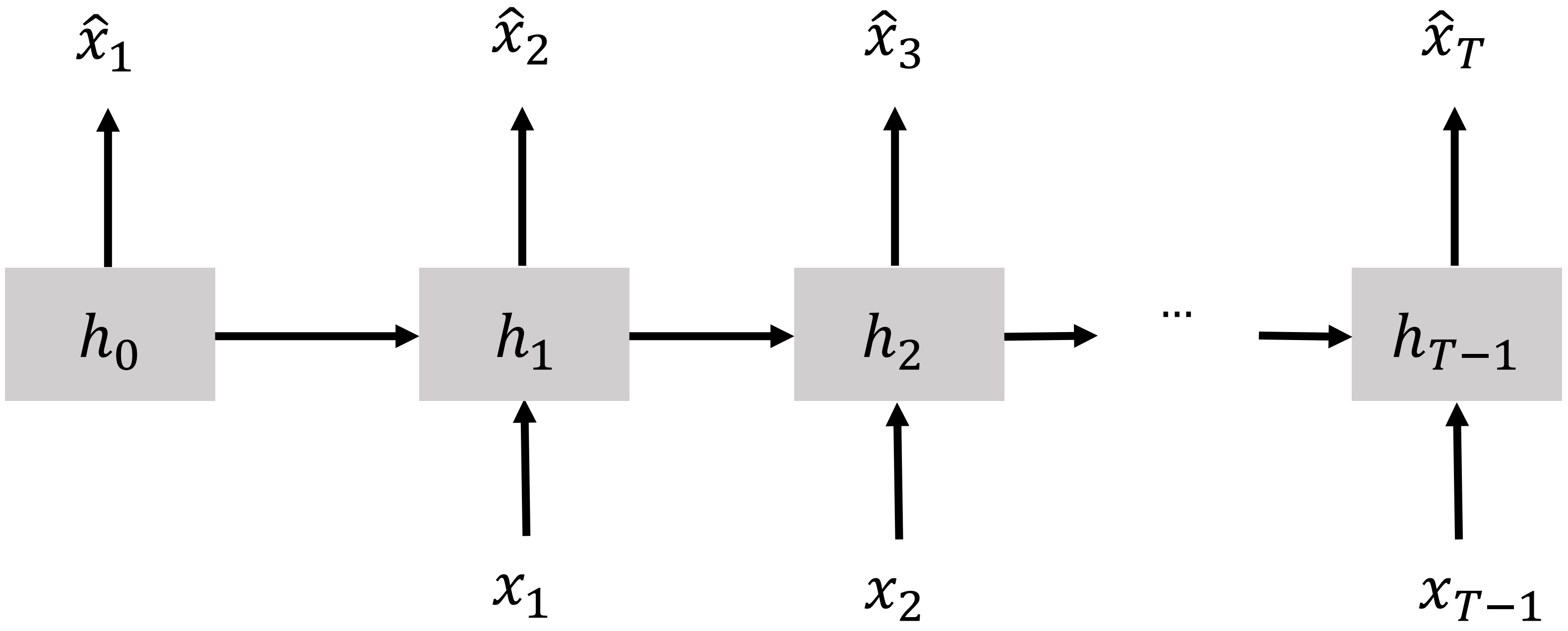


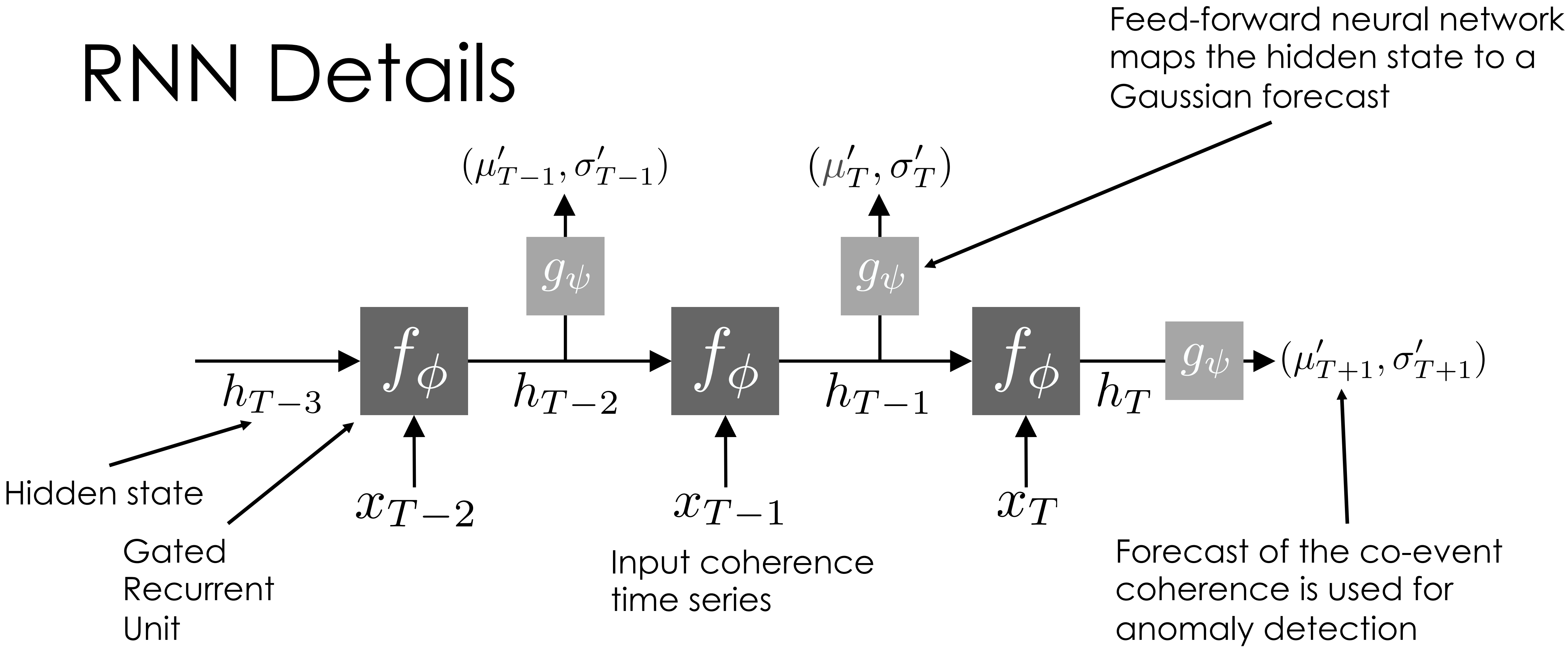


We can use Recurrent Neural Networks (RNNs) for anomaly detection



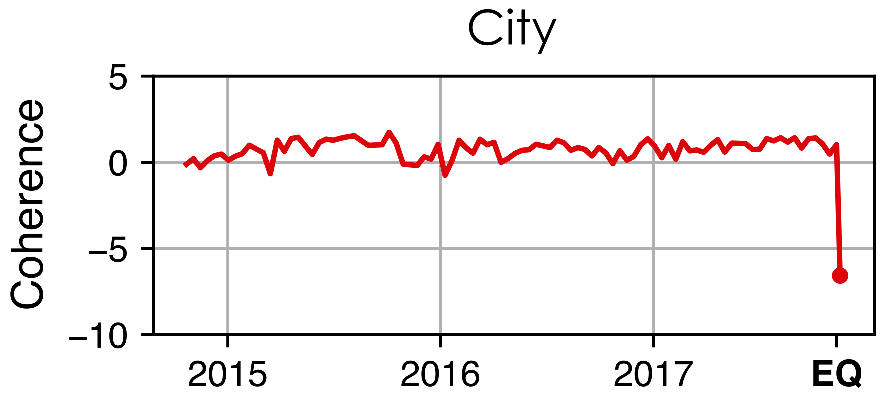
- Input sequence $\{x_1, x_2, \ldots, x_T\}$
- Hidden state h_t summarizes the sequence up to time t
- Compute h_t from x_t and h_{t-1}, then predict x_{t+1} from h_t
- Train on many time series to make the 'best' prediction

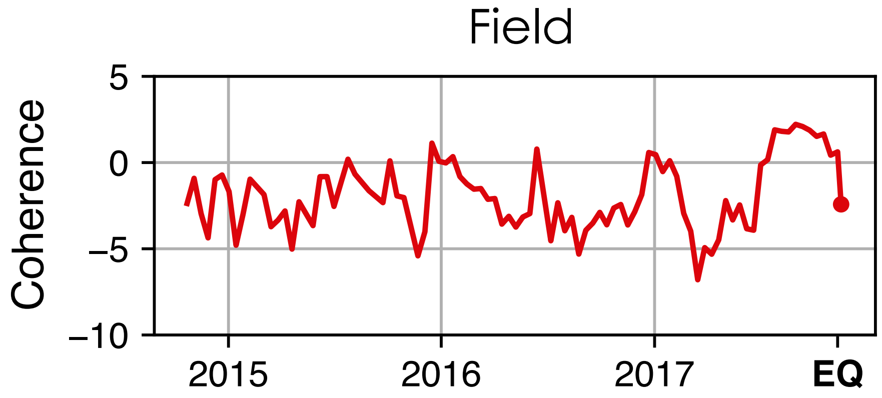
RNN Details



- Total of ~250,000 trainable parameters

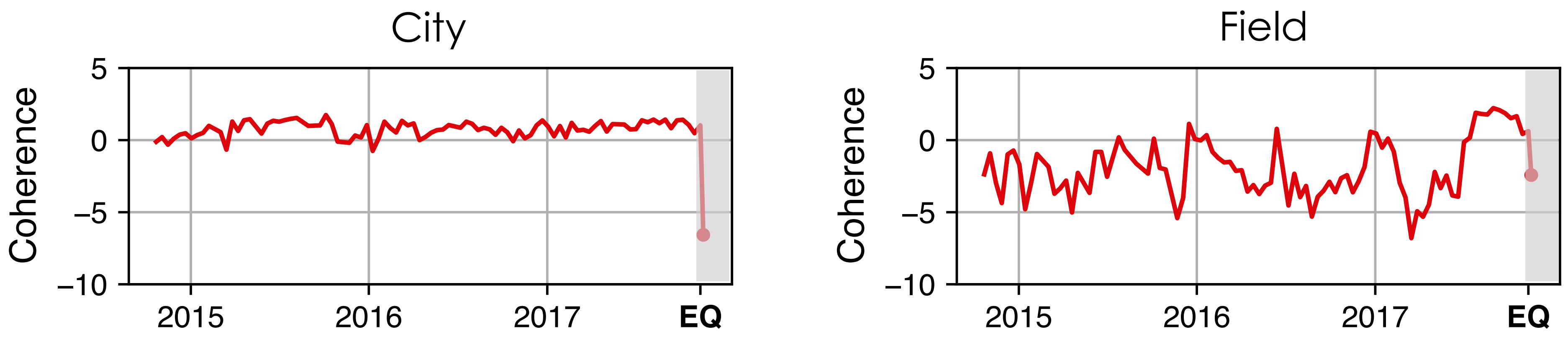
Train an RNN on many pre-event coherence time series





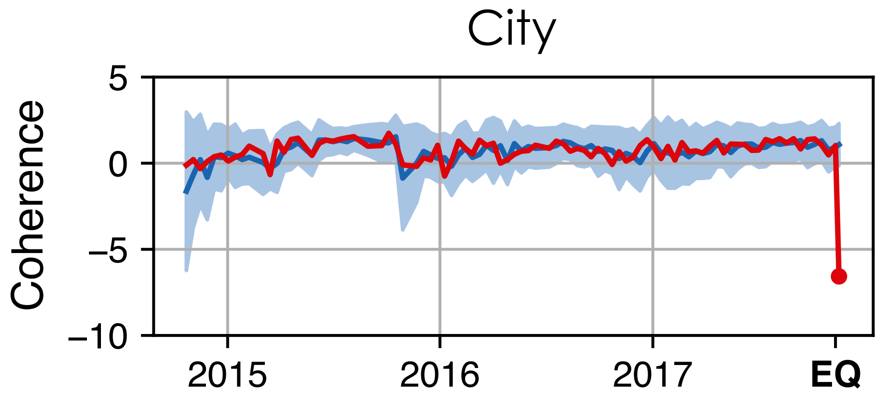
Train on ~3,000,000 coherence time series from the geographic region in which we're doing damage detection

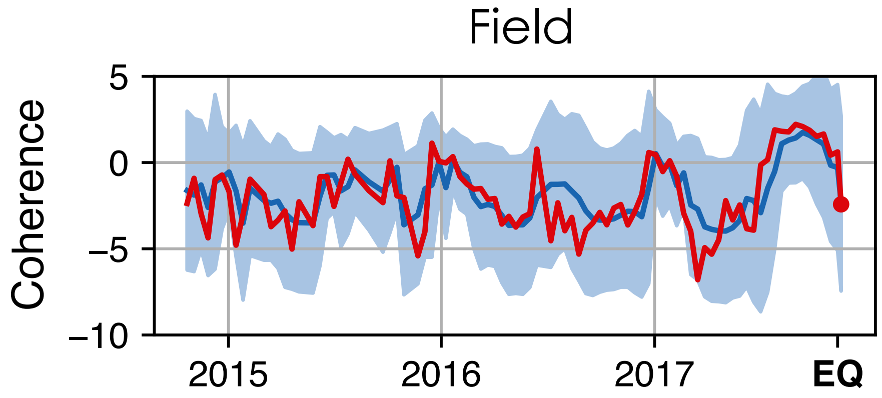
Train an RNN on many pre-event coherence time series



Exclude the co-event coherence during training. We don't want to train on the anomaly!

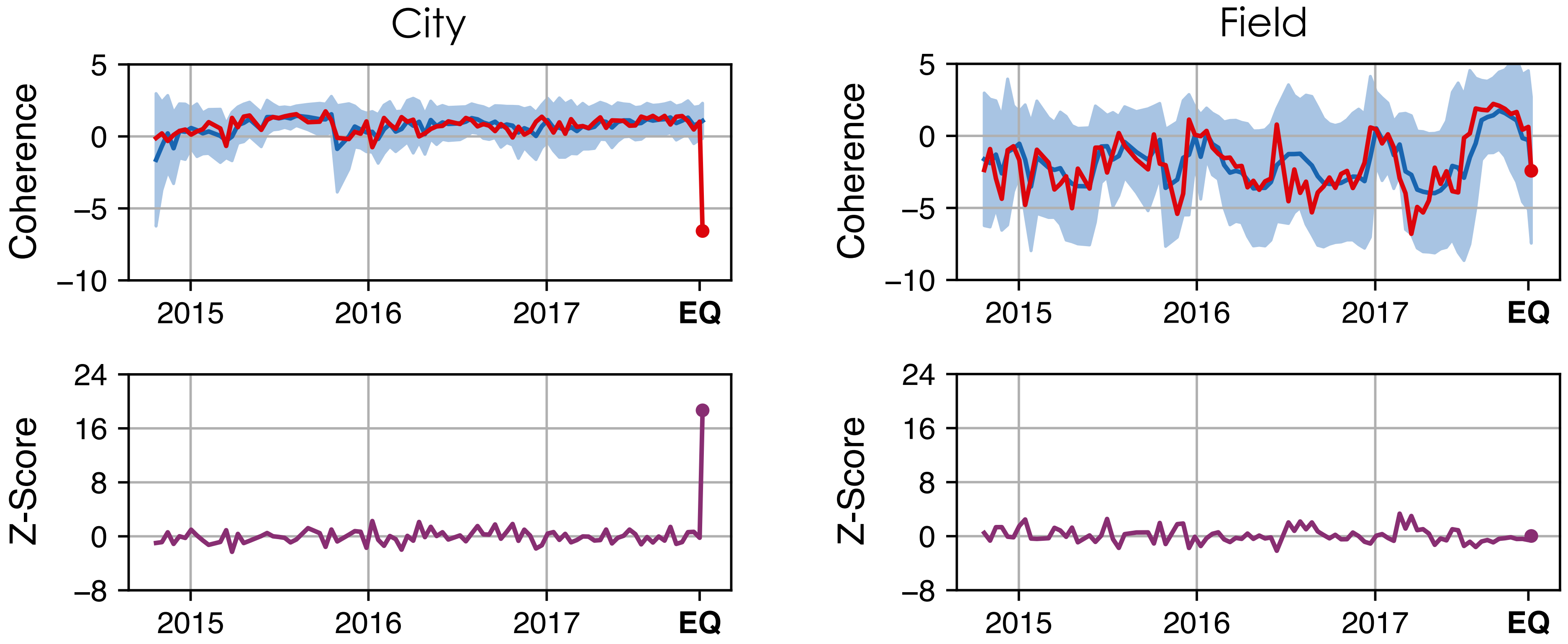
Use the trained RNN to forecast the co-event coherence





At each step, make a Gaussian forecast for the coherence

Compute the deviation from the forecast to detect anomalies

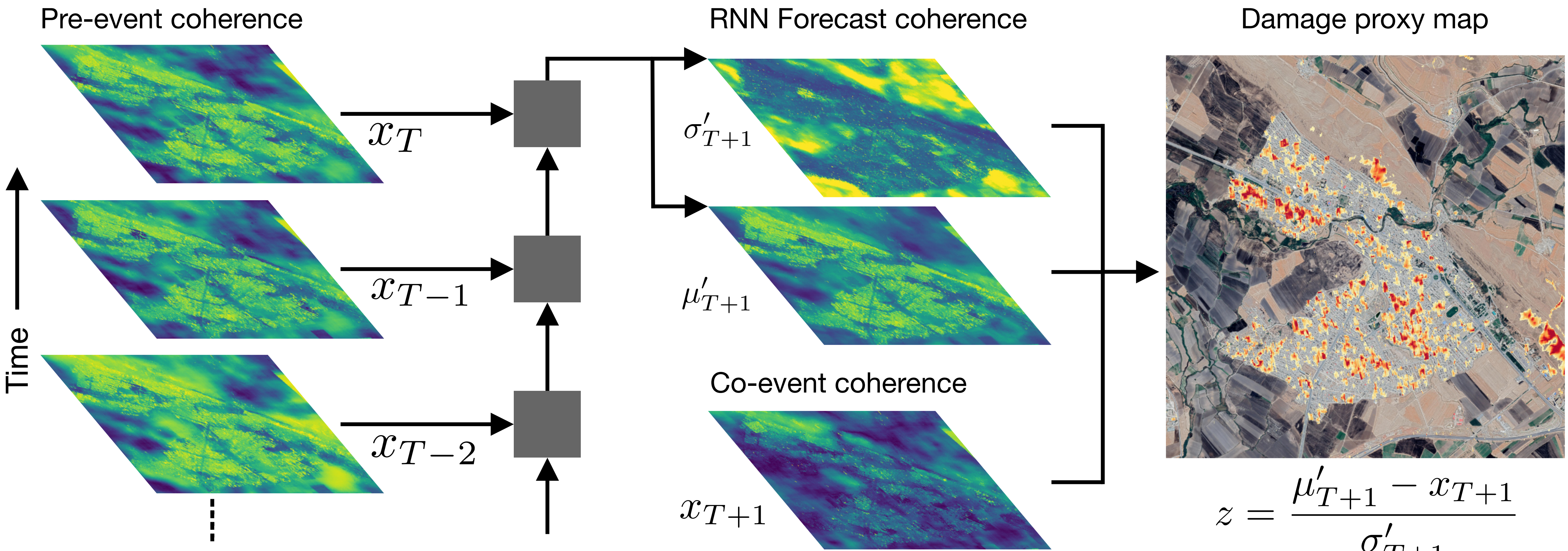


Use the co-event z-score as a proxy for damage

$$z = \frac{\mu'_{T+1} - x_{T+1}}{\sigma'_{T+1}}$$

Overall Method Summary

Observe coherence behavior pre-event → **Train RNN to forecast normal coherence** → **Compare forecast to observed co-event coherence** → **Form damage proxy map from anomalous coherence**



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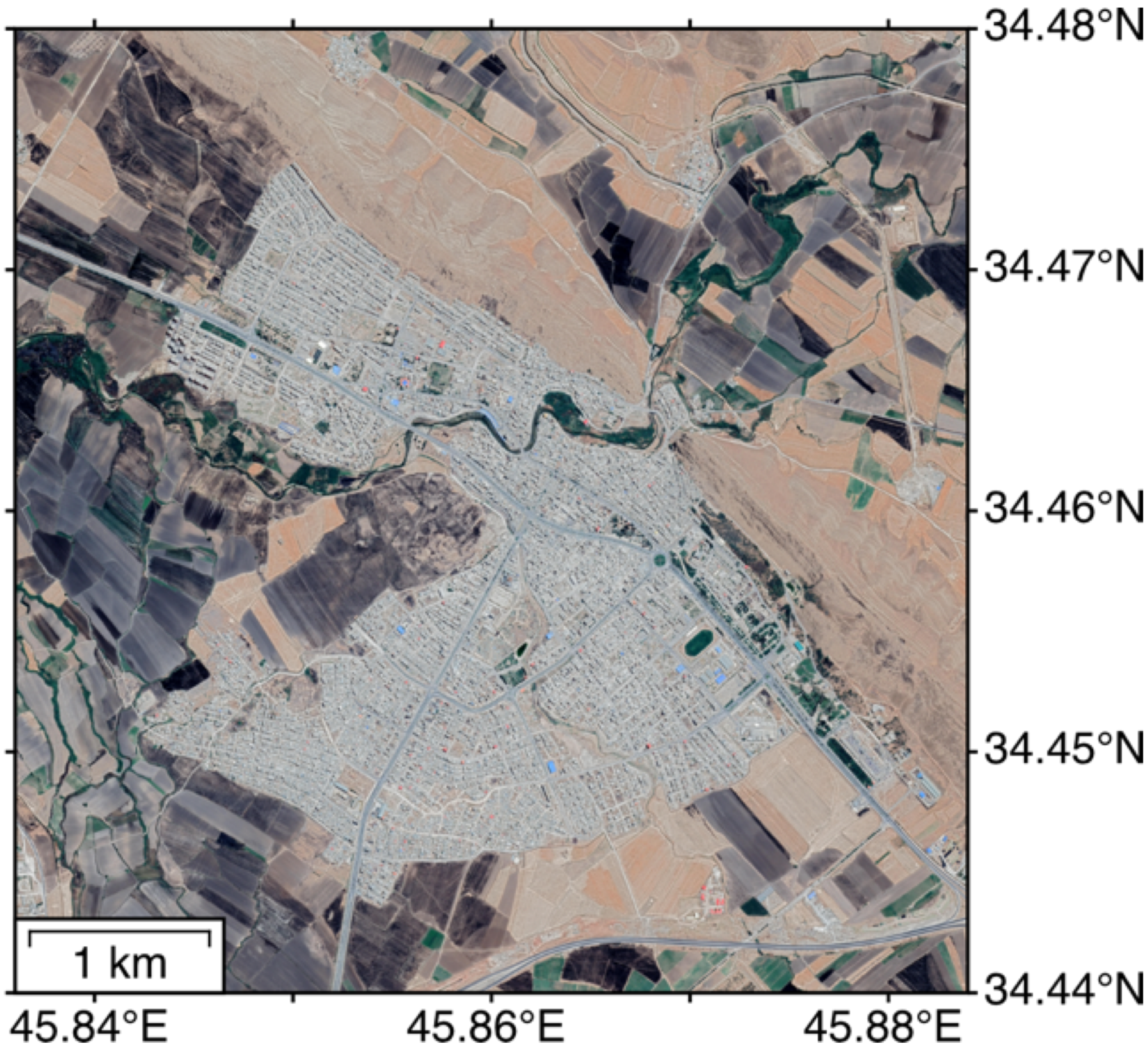
Optical data: Google/CNES/Airbus



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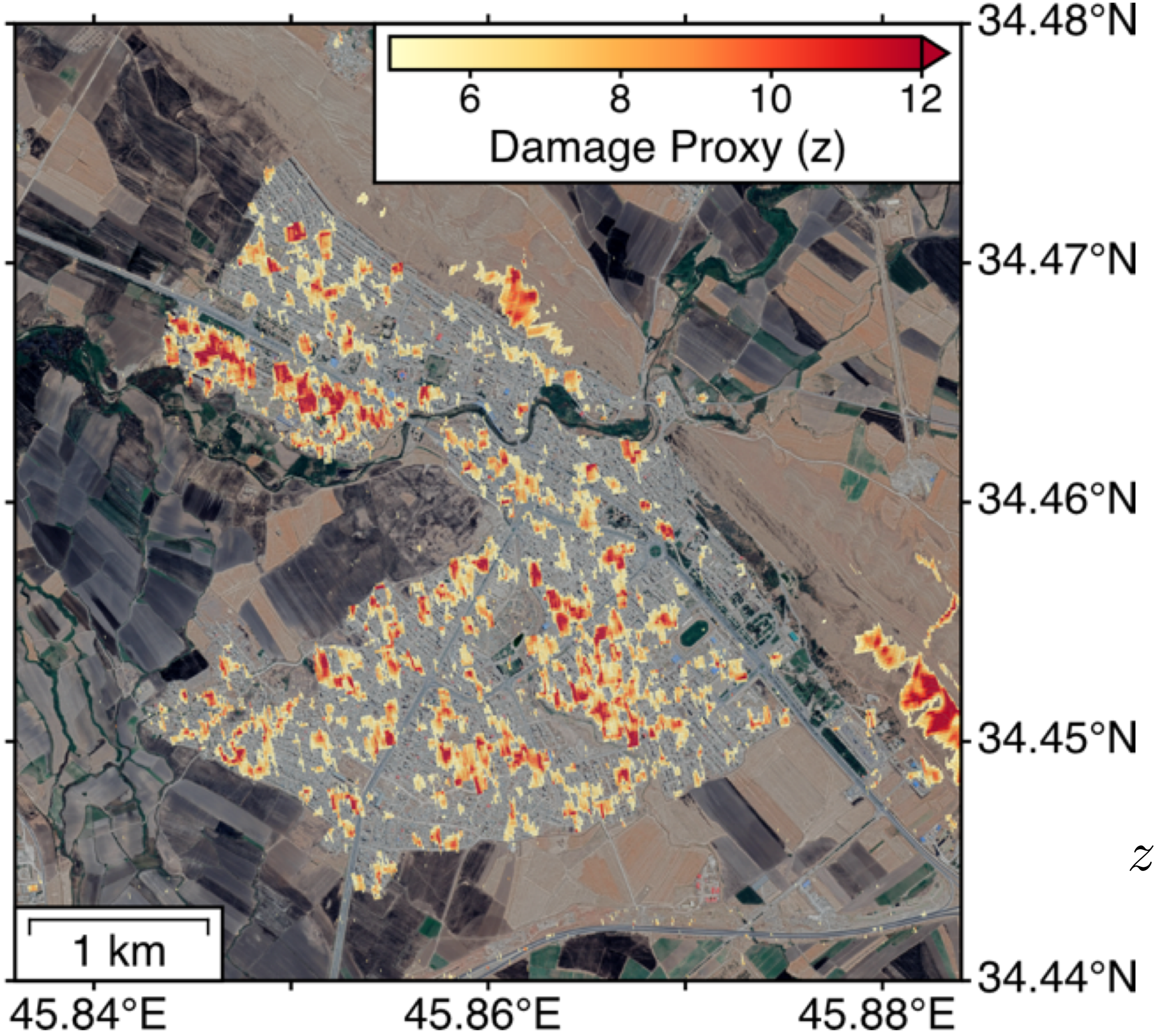

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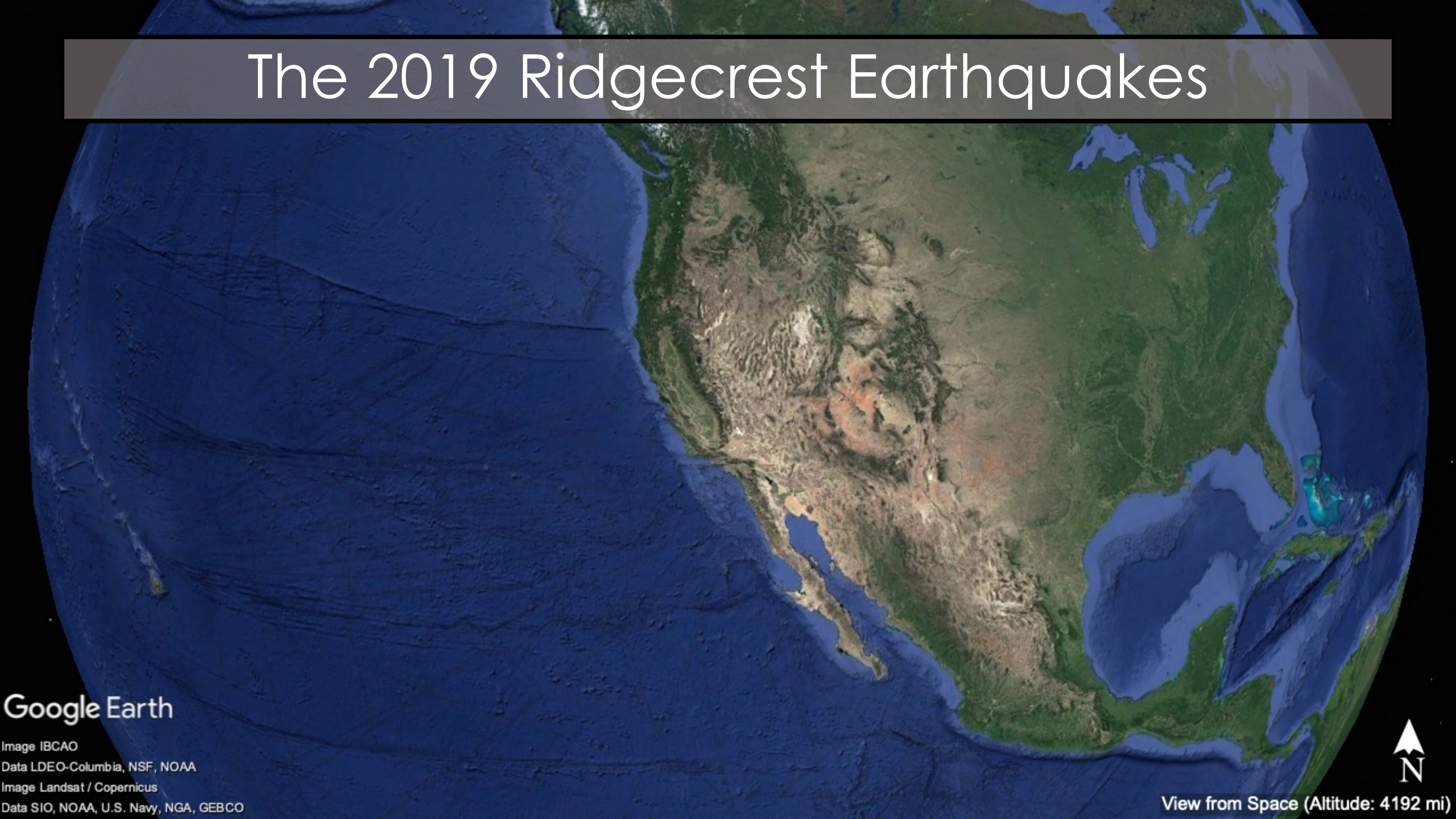
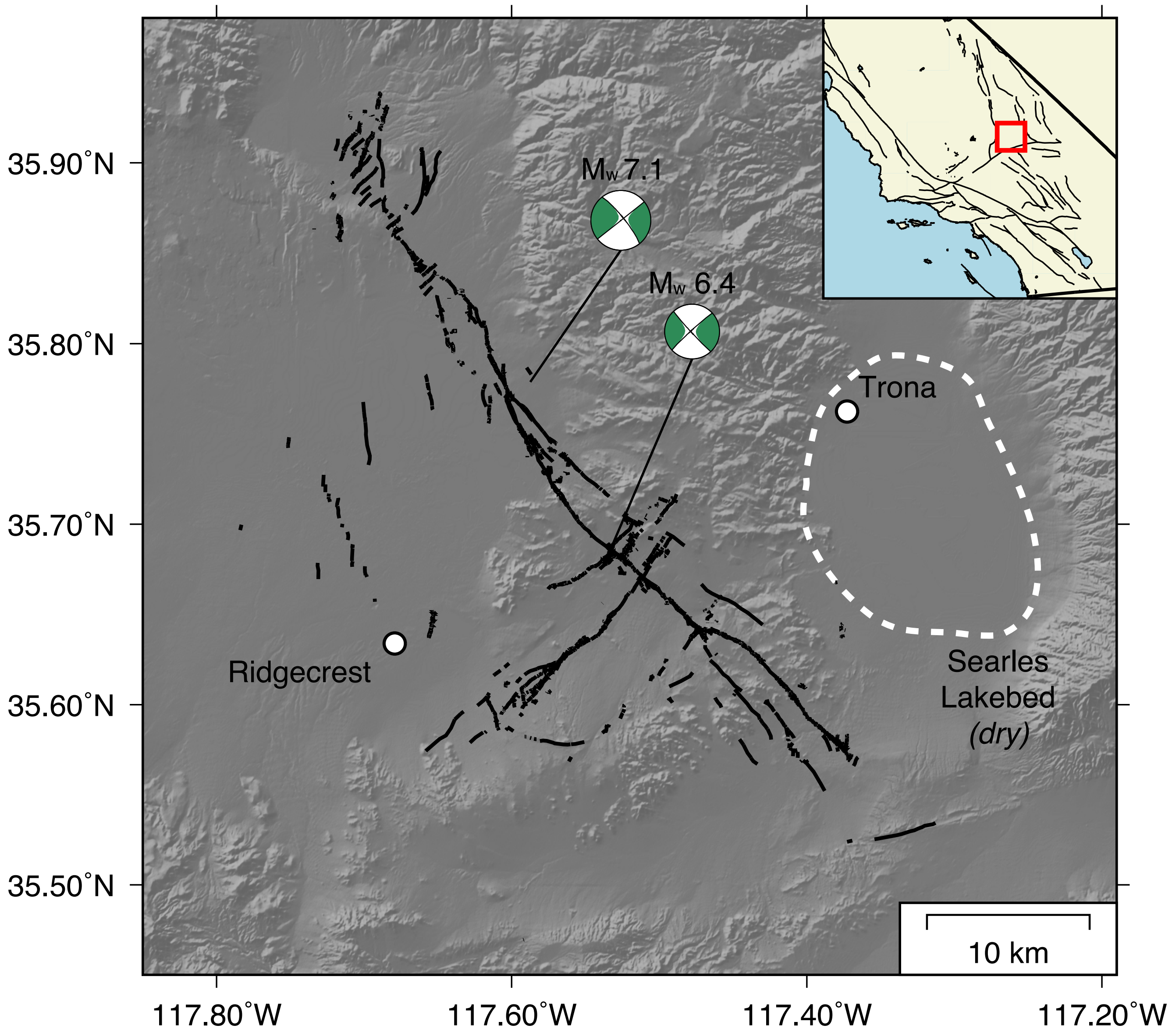
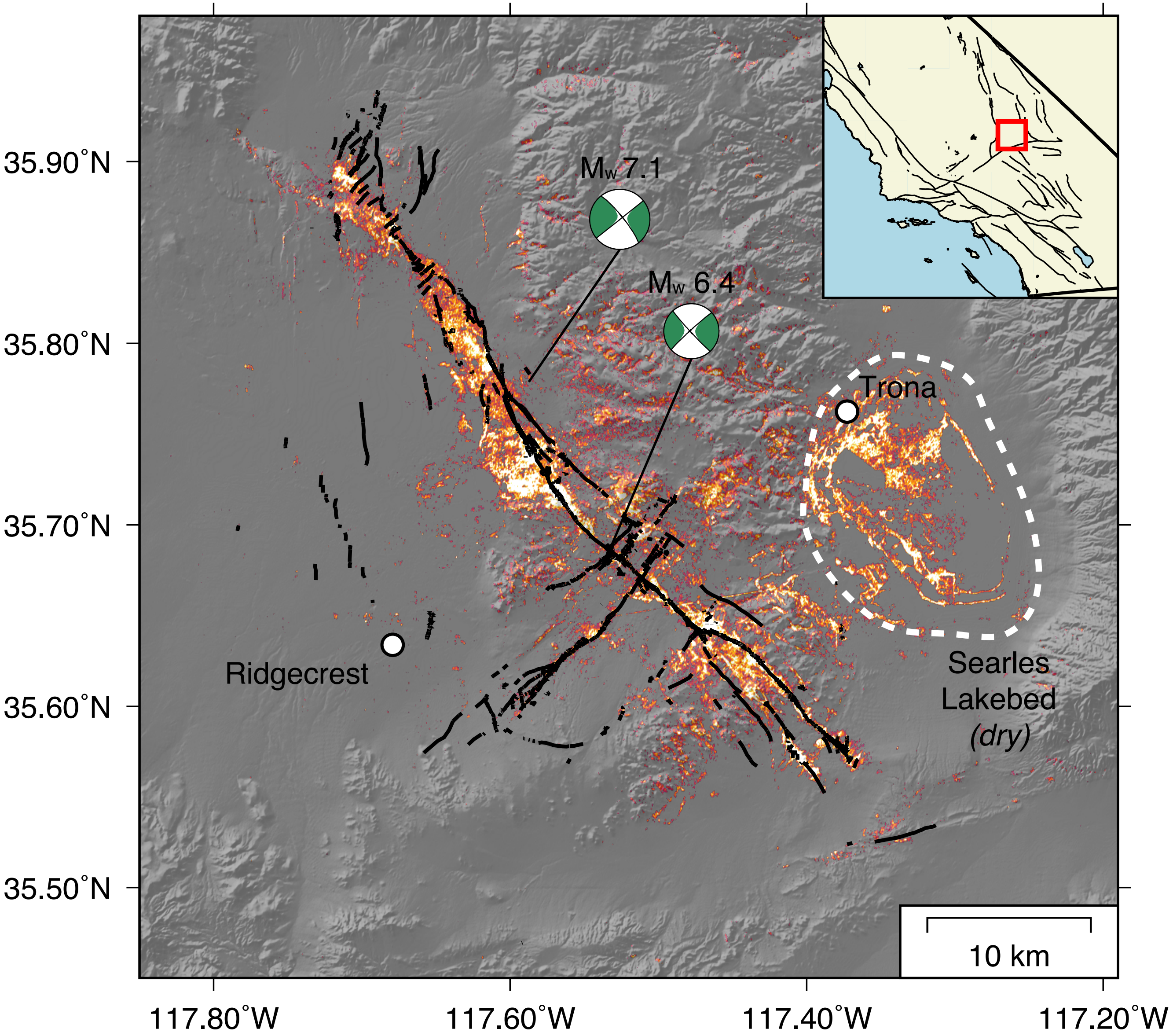
The 2019 Ridgecrest Earthquakes





35.90°N
35.80°N
35.70°N
35.60°N
35.50°N
117.80°W
117.60°W
117.40°W
117.20°W
Mw 7.1
Mw 6.4
Trona
Ridgecrest
Searles
Lakebed
(dry)
10 km

Photos: USGS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35.90˚N
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35.70˚N
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117.80˚W
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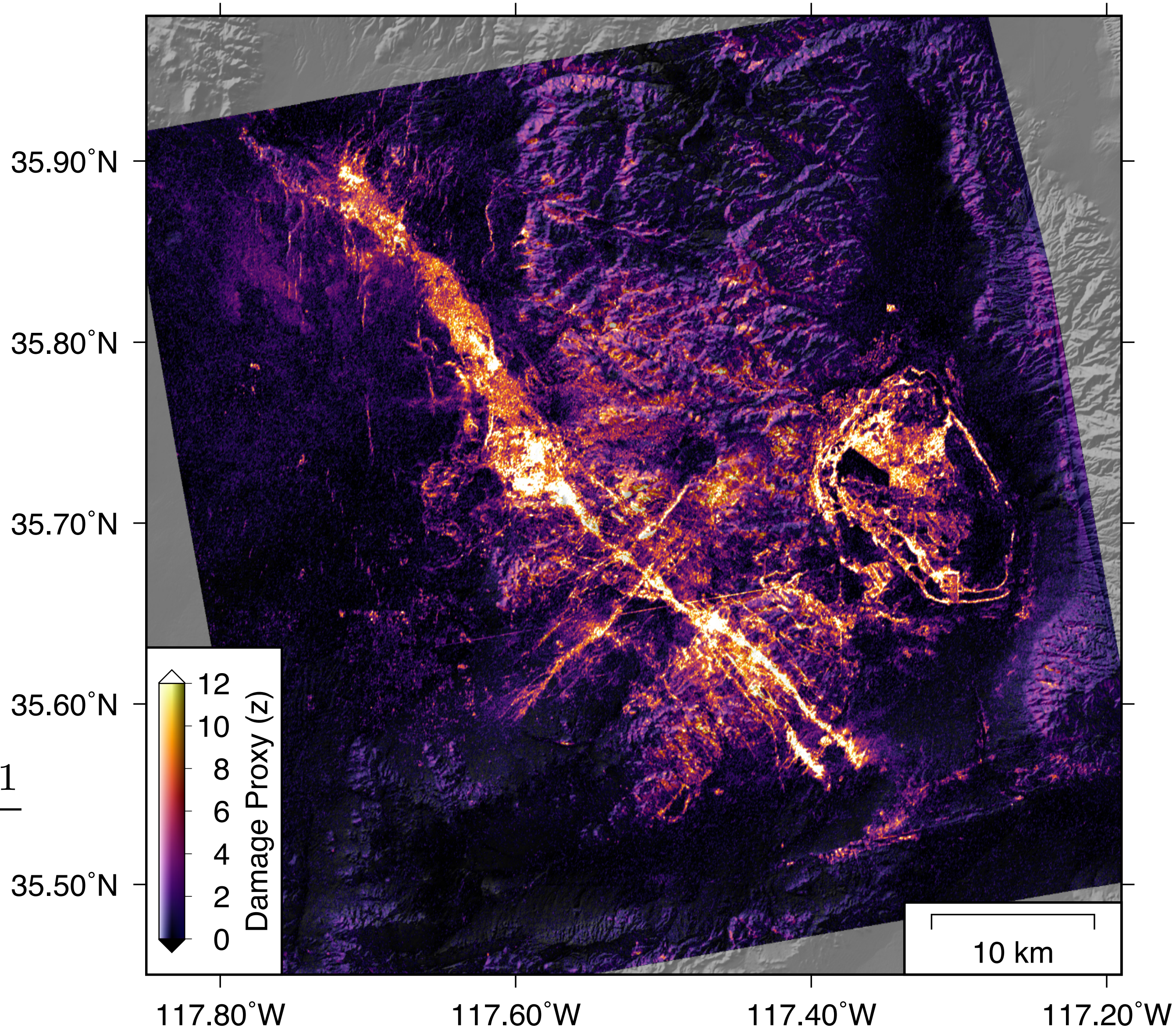
Photos: USGS

$$z = \frac{\mu'_{T+1} - x_{T+1}}{\sigma'_{T+1}}$$



Photos: USGS

Key Points

1. Synthetic aperture radar (SAR) can see through clouds, day and night, and data is becoming increasingly available
2. We can frame the damage mapping problem as one of detecting anomalies in sequential SAR observations of the ground
3. Our approach uses Recurrent Neural Networks to forecast the co-event coherence and compare with observations
4. These damage maps can be used to direct emergency response

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